Optimal Beaconing Control in Delay-Tolerant Networks With Multiple Destinations

Yahui Wu, Su Deng, and Hongbin Huang

Abstract—**The opportunistic contacts between nodes have important impact on the routing process in delay-tolerant networks, and they are related to the *beaconing rate*. In this paper, we study the optimal *beaconing rates* for the relay nodes and destinations at the same time. First, a theoretical framework, which can be used to evaluate the performance under different beaconing policies, is presented. Then based on the framework, we formulate an optimization problem. Through Pontryagin's maximum principle, we obtain the optimal beaconing policies for the relay nodes and destinations, respectively. In addition, we prove that both optimal policies conform to the *threshold* form. The optimal policy of the relay nodes changes its value from the maximal *beaconing rate* to the minimal one, but it is opposite for the destinations. The simulations show the accuracy of our theoretical model. Extensive numerical results show that the optimal policies are really better.**

Index Terms—**Beaconing rate, delay-tolerant networks (DTNs), limited energy, multiple destinations, optimal control.**

I. Introduction

Nodes in traditional mobile ad hoc networks often cooperate to establish network connectivity and then perform the corresponding routing algorithms without the help of infrastructure. However, the assumption for traditional ad hoc networks as connected graph may not be applicable to some existing and emerging wireless networks, where there may be no contemporaneous end-to-end paths between the source and destination pairs due to a variety of reasons such as node mobility and sparse node density. At present, the concept of delay-tolerant networks (DTNs) is proposed to support those wireless applications [1]. In particular, DTNs have been used in many cases such as deep space exploration [2], mobile social networks [3], and communication in disaster environment [4]. Routing algorithms in traditional ad hoc networks, which rely on the end-to-end path, cannot work in DTNs efficiently.

In order to overcome the network partitions, nodes in DTNs communicate in a *store–carry–forward* way. When the next hop is not immediately available for the current node, some relay nodes will *store* the message in their buffer, *carry* the message along their movements, and *forward* the message to others when a new communication opportunity occurs. Obviously, such method closely depends on the opportunistic contacts between nodes, which are further related to the *beaconing rate* of nodes. In particular, bigger *beaconing rate* can bring more contacts, but more energy will be needed. On the other hand, due to the uncertainty of communication opportunities in DTN, routing algorithms often create multiple copies of the same message and forward these copies to different nodes to increase the chance that the destinations get the message. The most typical one of those algorithms is the epidemic routing (ER) protocol, which works in a flooding way, and nodes carrying a message will forward the copies of the message to all neighbors [5]. Although ER algorithm can make the information spread fast, it uses too much energy due to the blind flooding nature. Therefore, if we want to get better performance, more energy may be consumed. In many applications, the energy budget is limited; hence, how to get the best performance with limited energy is an important problem [6]. This problem can be divided into some different cases, for example, the optimal forwarding problem and the optimal beaconing problem. In the optimal forwarding problem, the core is to find the optimal probability that nodes forward message to others at every instant. Similarly, in the optimal beaconing problem, the object is to find the optimal *beaconing rate* of the nodes.

At present, many works have been proposed, and they study the optimal forwarding problem from different aspects. For example, the work in [7] is the first to explore such problem, and it introduces a discrete-time model to describe the message-spreading process. Then based on the model, it analyzes the optimal forwarding policy and proves that the optimal policy conforms to the *threshold* form. The work in [8] studies similar problem based on the continuous-time model and proves that the optimal policy still conforms to the *threshold* form. Khouzani *et al.* extend previous works and study the optimal forwarding policy when nodes have heterogeneous energy budget [9]. The work in [10] introduces an optimal forwarding problem when nodes may be selfish. On the other hand, there are some works that explore the optimal forwarding problem to get the tradeoff between the performance and energy consumption. In this case, the total energy budget is not significantly limited. Therefore, this problem is an optimization problem without obvious constraint. For example, the work in [11] studies the tradeoff between the message delay and the energy consumption, and it proves that the optimal forwarding policy conforms to the *threshold* form. The work in [12] explores the optimal forwarding policy when the source may not have perfect knowledge of the delivery status at every instant. However, to make the problem simpler, the work in [12] just considers the two-hop routing protocol [13].

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Compared with the optimal forwarding problem, there are fewer works about the optimal beaconing problem in DTNs. The work in [14] introduces a joint beaconing and forwarding problem, but it only uses the two-hop routing protocol, which is too simple. The work in [15] explores the optimal beaconing problem with ER protocol. Then, the work in [16] studies the joint forwarding and beaconing policies based on the ER algorithm. However, all of the above works assume that there is only one destination, and the energy consumption for the destination can be ignored in this case. In many applications, there may be multiple destinations; hence, optimal control with multiple destinations is necessary. Because the energy consumption of the destination is often ignored when there is only one destination, the energy is mainly used by the relay nodes. In this case, we just need to consider the optimal beaconing policy for the relay nodes. However, when there are multiple destinations, the energy consumption for the destinations cannot be ignored and the optimal control problem will be more complex. For example, if the relay nodes use the minimal *beaconing rate*, much energy will be saved. However, the relay nodes are hard to detect others in this case. Furthermore, they are hard to get the message from others; thus, the destinations can get the message from fewer nodes, and the probability is smaller. Therefore, although there is much energy, there may not be enough time to use it. On the other hand, if the relay nodes use the maximum *beaconing rate* all the time, they have bigger probability to get the message. Therefore, the destinations may get the message from more nodes and the probability is bigger. However, the rest of the energy is small and may not be enough to forward the message to the destinations. This means that when exploring the optimal beaconing policy for the relay nodes, we have to consider whether there is enough energy for the destinations; thus, the control problem is more complex. In addition, since the energy consumption for the destinations cannot be ignored when there are multiple destinations, exploring the optimal beaconing policy for the destinations is necessary. In this case, we have to classify the *beaconing rates* according to the roles of the nodes (relay nodes or destinations), and the optimization problem has two controlling parameters. This makes the optimal controlling problem much more complex. The work in [17] considers the optimal controlling problem in DTNs with multiple destinations. However, this work is oriented to the optimal forwarding policy, which ignores the energy consumption in the beaconing process. In addition, it just studies the forwarding policy for the relay nodes, and the optimization problem only has one parameter. The work in [18] studies the optimal beaconing problem with multiple destinations, but it does not consider the limited energy.

In this paper, we study the optimal beaconing policies in DTNs with multiple destinations when the total energy is limited. In particular, we study the optimal *beaconing rates* for the relay nodes and destinations, respectively. To the best of our knowledge, we are the first to explore such problem. In this paper, a theoretical framework, which can be used to analyze the performance under different beaconing policies, is presented. Then we formulate an optimization problem, in which the controlling parameters are the *beaconing rates* for the relay nodes and destinations. Through Pontryagin's maximum principle, we obtain the optimal beaconing policies and prove that both the optimal policies conform to the *threshold* form. In other words, the optimal policies have a *bang-bang* structure and have at most one jump. The *bang-bang* structure means that the controlling parameters (*beaconing rates*) just adopt the boundary values (i.e., the maximal value 1 and the minimal value 0), and they can be any value only when they change from one boundary to another [19]. The *jump* denotes the point where the value of the controlling parameters (*beaconing rates*) changes. The jumping process for the relay nodes is opposite for the destinations. For example, the relay nodes first have the maximal *beaconing rate*, and then change to the minimal *beaconing rate*, but the optimal policy of the destinations jumps from the minimal value to the maximal value. In this case, the relay nodes will beacon with the maximum rate before certain time and then with the minimal rate in the rest time. However, the destinations will first beacon with the minimal rate and then with the maximal value in the rest time. We check the accuracy of our theoretical framework through simulations. In addition, we compare the performance of the optimal policies with certain other policies through extensive numerical results and find that the optimal policies obtained by our model are better.

Note that this paper just considers the optimal beaconing problem similar to the work in [15]. The joint forwarding and beaconing control will be our future work. However, we do not ignore the energy consumption in the forwarding process.

The rest of this paper is organized as follows. In Section II, we describe the network model. In Section III, we first present the theoretical model and then solve the corresponding optimal controlling problem. In Section IV, we introduce the simulation and numerical results. Finally, we conclude our main work in Section V.

II. Network Model

We suppose that the network has N relay nodes and M destinations. Among these relay nodes, there is a source S, and only S has a message at time 0. The maximal lifetime of the message is T, and the message is useless after time T. We use the ER protocol to forward the message; hence, the nodes will forward the message to all of their neighbors. The main symbols used in this paper are shown in Table I.

The message can be transmitted only when nodes meet each other, which means a contact; thus, the mobility rule of nodes is critical. In this paper, we assume that nodes move according to the exponential model, in which the intermeeting time between two consecutive contacts conforms to the exponential distribution. At present, some works show that the exponential model may not be accurate and present many new models such as the Home-MEG model [20] and the edge–Markov model [21]. These models are more accurate in some scenarios, but we still use the exponential model for two reasons. First, the mobility patterns of nodes are very sophisticated and cannot be captured well by a simple mobility model. In other words, there is no general model that can fit all of the mobility laws. Second, the exponential model is accurate in some cases. For example, the work in [22] finds that if considering long traces,

TABLE I
VARIABLES SUMMARY

Symbol	Explanation
N	Number of relay nodes
M	Number of destinations
T	Maximal lifetime of the message
$\mu(t)$	Beaconing rate of the relay nodes at time t
$\varepsilon(t)$	Beaconing rate of the destinations at time t
γ	Death rate of the nodes due to energy empty
$X(t)$	Number of the relay nodes carrying the message at time t
$Y(t)$	Number of the relay nodes without message stay in the network at time t
$U(t)$	Number of the destinations carrying the message at time t
$V(t)$	Number of the destinations without message stay in the network at time t
$C(t)$	Energy consumption up to time t
λ_X	Co-state that corresponds to state $X(t)$
λ_Y	Co-state that corresponds to state $Y(t)$
λ_U	Co-state that corresponds to state $U(t)$
λ_V	Co-state that corresponds to state $V(t)$

the tail of the distribution is exponential. The work in [23] shows that the intermeeting time can be shaped to be exponential by choosing an approximate domain size. Moreover, there are also some works that describe the intermeeting time of human or vehicles by exponential distribution and validate their model experimentally on real motion traces [24], [25]. For these reasons, we use the exponential model similar to most of the existing works [6]–[15]. In particular, we assume that if nodes use the biggest *beaconing rate*, the intermeeting time between two nodes follows an exponential distribution with the parameter denoted by λ. Then, we define $\mu(t)$ and $\varepsilon(t)$ as the *beaconing rates* for the relay nodes and the destinations at time t, respectively. In addition, we have $0 \leq \mu(t)$, $\varepsilon(t) \leq 1$, where 0 is the minimal *beaconing rate*. If $\mu(t) = 1$ and $\varepsilon(t) = 1$, all nodes have the biggest *beaconing rate*; thus, nodes encounter each other with parameter λ. On the other hand, under the *beaconing rates* $\mu(t)$ and $\varepsilon(t)$, the relay nodes detect others with rate $\lambda\mu(t)$ and the destinations detect others with rate $\lambda\varepsilon(t)$ (denoted by contact rate or detect rate). In fact, the *beaconing rate* can be seen as the probability that nodes really beacon to find others. For example, if $\mu(t) = 1$, the relay nodes beacon to find others. However, if $\mu(t) = 0$, the relay nodes switch off their beaconing device. Given the time interval $[t, t + \Delta t]$, a relay node detects others with probability $1 - \mathrm{e}^{-\lambda\Delta t}$ if it beacons. At time t, the probability that the relay nodes beacon is $\mu(t)$; thus, a relay node detects others with probability$\mu(t)(1 - \mathrm{e}^{-\lambda\Delta t})$. If we take the limitation for Δt, we can get $\lambda\mu(t)$. For this reason, we say that the relay nodes detect others with rate $\lambda\mu(t)$ at time t. Similarly, the rate of the destinations is $\lambda\varepsilon(t)$ at time t.

In addition, we assume that a node exhausts its energy and leaves from the network according to the exponential distribution and the basic death rate of the node is $\gamma(\geq 0)$ [14], [15]. Under the *beaconing rates* $\mu(t)$ and $\varepsilon(t)$, the death rates of the relay nodes and destinations are $\mu(t)\gamma$ and $\varepsilon(t)\gamma$ [14], [15], respectively.

In the network, there may be many different messages. However, in this paper, we only consider one message similar to most of the previous works, such as [6]–[15]. Existing studies have shown that the communication energy consumption mainly includes the *transmitting consumption* in the communication state and the *beaconing consumption* in the idle state [26]. Therefore, we mainly consider the energy consumption in the transmission and beaconing processes similar to [14] and [15]. Obviously, each transmission will make a node get the message; hence, the energy consumption is proportional to the number of nodes that get the message from others.

We let $X(t)$ and $U(t)$ denote the numbers of the relay nodes and destinations that have the message at time t, respectively. Similarly, $Y(t)$ and $V(t)$ denote the numbers of the relay nodes and destinations that do not have the message and stay in the network at time t, respectively. Therefore, we have $X(0) = 1$, $U(0) = 0$, $Y(0) = N - 1$, and $V(0) = M$. In fact, all of these symbols are stochastic variables related to $\mu(t)$ and $\varepsilon(t)$; hence, we consider their expected value. Up to time t, the expectation of the number of nodes, which get the message from others, is $E(X(t)) + E(U(t)) - 1$ (the source has the message at time 0, and it does not receive the message from others); therefore, the average transmission time is $E(X(t)) + E(U(t)) - 1$. In this case, the total energy consumption for message transmission can be expressed as $\alpha(E(X(t)) + E(U(t)) - 1)$ [14], [15]. α is a positive multiplication. For the beaconing process, we assume that once a node obtains the message, it will stop beaconing to save energy. In other words, only those nodes that do not have message keep beaconing to find others, and similar assumption has been used in [14] and [15]. Therefore, the *beaconing* energy consumption is proportional to the *beaconing rate* and the number of nodes that do not have message and stay in the network. Furthermore, similar to [14] and [15], we can get the average *beaconing* energy consumption as follows:

$$\beta \int_0^T (\mu(t)E(Y(t) + \varepsilon(t)E\left(V(t)\right) dt. \tag{1}$$

β is the system-specified positive constant that weights the energy consumption of each beaconing. Combining the energy consumption in the transmitting process, we can get the total cost of the energy as follows.

$$E\left(C(T)\right) = \alpha\left(E\left(X(T) + E(U(T)\right) - 1\right) + \beta \int_0^T (\mu(t)E(Y(t) + \varepsilon(t)E\left(V(t)\right) dt. \tag{2}$$

Now, our object is to solve the following optimization problem:

$$\begin{cases} \text{Maximize } E\left(U(T)\right) \\ E\left(C(T)\right) \leq B. \end{cases} \tag{3}$$

B denotes the total energy budget that can be used. $E(U(T))$ denotes the average number of the destinations that get the message up to time T.

III. Problem Formulation

A. Message-Spreading Model

Note that $X(t)$ denotes the number of relay nodes that have the message at time t. Given a small time interval Δt, we have [14], [15]

$$X(t+\Delta t) = X(t) + \sum_{j\in\{Y(t)\}} \phi_j(t, t+\Delta t). \tag{4}$$

Symbol $\{Y(t)\}$ denotes the set of relay nodes that do not have the message and do not leave from the network at time t; thus, it has $Y(t)$ elements. $\varphi_j(t, t+\Delta t)$ denotes the event whether node j gets the message in time interval $[t, t+\Delta t]$. If $\varphi_j(t, t+\Delta t) = 1$, we say that this event happens, but if $\varphi_j(t, t+\Delta t) = 0$, the event does not happen. At time t, the number of nodes that have the message is $X(t) + U(t)$. In addition, nodes encounter each other according to the exponential distribution. In particular, at time t, the *beaconing rate* of the relay node j is $\mu(t)$, and the contact rate between nodes is $\lambda\mu(t)$. Therefore, node j encounters a specific node that has the message (e.g., k) in time interval $[t, t+\Delta t]$ with probability $\mu(t)(1-e^{-\lambda\Delta t})$. Furthermore, we have

$$\begin{aligned} p\left(\phi_j(t, t+\Delta t) = 1\right) &= 1 - \left(1-\mu(t)\left(1-e^{-\lambda\Delta t}\right)\right)^{X(t)+U(t)} \\ &= 1 - e^{-\lambda\mu(t)\Delta t(X(t)+U(t))}. \end{aligned} \tag{5}$$

Then, we can easily get the closed-form expression of (5), which is shown as follows:

$$\begin{aligned} E\left(\dot{X}(t)\right) &= E\left(Y(t)\right) \lim_{\Delta t\to 0} \frac{E\left(\phi_j(t, t+\Delta t)\right)}{\Delta t} \\ &= \lambda E\left(Y(t)\right)\left(E\left(X(t)\right) + E\left(U(t)\right)\right)\mu(t). \end{aligned} \tag{6}$$

For $Y(t)$, we have

$$\begin{aligned} Y(t+\Delta t) = Y(t) &- \sum_{j\in\{Y(t)\}} \phi_j(t, t+\Delta t) \\ &- \sum_{j\in\{Y(t)\}} \rho_j(t, t+\Delta t). \end{aligned} \tag{7}$$

When the nodes exhaust their energy, they cannot join in the message-transmitting process any more, and we say that they leave from the network. Symbol $\rho_j(t, t+\Delta t)$ denotes the event whether node j leaves from the network in time interval $[t, t+\Delta t]$. If $\rho_j(t, t+\Delta t) = 1$, we say that this event happens, but if $\rho_j(t, t+\Delta t) = 0$, the event does not happen. At time t, a relay node leaves from the networks according to the exponential distribution with rate $\mu(t)\gamma$; therefore, we have

$$p\left(\rho_j(t, t+\Delta t) = 1\right) = 1 - e^{-\gamma\mu(t)\Delta t}. \tag{8}$$

Furthermore, we have,

$$\begin{aligned} E\left(\dot{Y}(t)\right) = &-\lambda\left(E\left(X(t)\right) + E\left(U(t)\right)\right)E\left(Y(t)\right)\mu(t) \\ &-\gamma E\left(Y(t)\right)\mu(t). \end{aligned} \tag{9}$$

By the similar method, we can get the corresponding ordinary differential equations (ODEs) for the destinations. In particular, we have

$$\begin{cases} E\left(\dot{U}(t)\right) = \lambda\left(E\left(X(t)\right) + E\left(U(t)\right)\right)E\left(V(t)\right)\varepsilon(t) \\ E\left(\dot{V}(t)\right) = -\lambda\left(E\left(X(t)\right) + E\left(U(t)\right)\right)E\left(V(t)\right)\varepsilon(t) \\ \qquad\qquad - \gamma E\left(V(t)\right)\varepsilon(t). \end{cases} \tag{10}$$

B. Optimal Control

Now, we will solve the optimization problem in (3). Let $((C, X, Y, U, V), \mu, \varepsilon)$ be an optimal solution. In particular, at time t, the symbols C, X, Y, U and V denote the value of $E(C(t))$, $E(X(t))$, $E(Y(t))$, $E(U(t))$, and $E(V(t))$. Similarly, μ and ε denote the *beaconing rates* $\mu(t)$ and $\varepsilon(t)$, respectively.

According to [27], the Hamiltonian function can be obtained by the derivatives of the objective and constraint functions and the corresponding state functions. From (2) and (3), we can get the objective and constraint functions. From (6), (9), and (10), we can get the derivatives of the state functions. Then, we can get the Hamiltonian H, which is shown in

$$\begin{aligned} H &= \dot{U} + \lambda_C\dot{C} + \lambda_X\dot{X} + \lambda_Y\dot{Y} + \lambda_U\dot{U} + \lambda_V\dot{V} \\ &= (1+\lambda_U)\dot{U} + \lambda_X\dot{X} + \lambda_Y\dot{Y} + \lambda_V\dot{V} \\ &\quad + \lambda_C\left(\alpha(\dot{X}+\dot{U}) + \beta(\mu Y + \varepsilon V)\right) \\ &= (1+\lambda_U+\alpha\lambda_C)\dot{U} + (\lambda_X+\alpha\lambda_C)\dot{X} + \lambda_Y\dot{Y} \\ &\quad + \lambda_V\dot{V} + \lambda_C\beta(\mu Y + \varepsilon V) \\ &= \lambda(1+\lambda_U+\alpha\lambda_C)(X+U)V\varepsilon + \lambda(\lambda_X+\alpha\lambda_C)(X+U)Y\mu \\ &\quad + \lambda_Y\left(-\lambda(X+U)-\gamma\right)Y\mu \\ &\quad + \lambda_V\left(-\lambda(X+U)-\gamma\right)V\varepsilon + \lambda_C\beta(\mu Y + \varepsilon V). \end{aligned} \tag{11}$$

In the above equation, the symbols λ_X, λ_Y, λ_U, λ_V, and λ_C are the costate or adjoint functions [27]. Their derivatives can be easily obtained based on (11). For example, the derivative of λ_X is equal to the opposite value of the Hamiltonian function's partial derivative for the state X. Then, we can obtain

$$\begin{cases} \dot{\lambda}_X = -\frac{\partial H}{\partial X} = -\lambda(1+\lambda_U+\alpha\lambda_C)V\varepsilon \\ \qquad -\lambda(\lambda_X+\alpha\lambda_C)Y\mu + \lambda\lambda_Y Y\mu + \lambda\lambda_V V\varepsilon \\ \dot{\lambda}_Y = -\frac{\partial H}{\partial Y} = -\lambda(\lambda_X+\alpha\lambda_C)(X+U)\mu \\ \qquad +\lambda_Y(\lambda(X+U)+\gamma)\mu - \lambda_C\beta\mu \\ \dot{\lambda}_U = -\frac{\partial H}{\partial U} = -\lambda(1+\lambda_U+\alpha\lambda_C)V\varepsilon \\ \qquad -\lambda(\lambda_X+\alpha\lambda_C)Y\mu + \lambda\lambda_Y Y\mu + \lambda\lambda_V V\varepsilon \\ \dot{\lambda}_V = -\frac{\partial H}{\partial V} = -\lambda(1+\lambda_U+\alpha\lambda_C)(X+U)\varepsilon \\ \qquad +\lambda_V(\lambda(X+U)+\gamma)\varepsilon - \lambda_C\beta\varepsilon \\ \dot{\lambda}_C = -\frac{\partial H}{\partial C} = 0. \end{cases} \tag{12}$$

The *transversality* conditions are shown as follows [27]:

$$\begin{aligned} &\lambda_X(T) = \lambda_Y(T) = \lambda_U(T) = \lambda_V(T) = 0 \\ &\lambda_C(T)\left(E\left(C(T)\right) - B\right) = 0,\ \lambda_C(T) \le 0. \end{aligned} \tag{13}$$

Then, according to Pontryagin's maximum principle [27, p. 109, Theorem 3.14], there exist continuous or piecewise continuously differentiable state and costate functions, which satisfy

$$(\mu, \varepsilon) \in \arg \max_{0\leq(\mu^*,\varepsilon^*)\leq 1} H\left(\lambda_C, \lambda_X, \lambda_Y, \lambda_U, \lambda_V, (C, X, Y, U, V), \mu^*, \varepsilon^*\right). \quad (14)$$

This equation denotes that maximizing the value of the objective function $E(U(T))$ is equal to maximizing the corresponding *Hamiltonian* H. In particular, at given time t, the state (C, X, Y, U, V) and *costate* $(\lambda_C, \lambda_X, \lambda_Y, \lambda_U, \lambda_V)$ can be seen as constants, and μ and ε can maximize H at this time. Based on (11), we can get the optimal beaconing policies of relay nodes and destinations, which are shown as follows:

$$\mu = \begin{cases} f = \partial H/\partial \mu \\ \quad = \lambda(\lambda_X + \alpha\lambda_C)(X + U) \\ \qquad + \lambda_Y\left(-\lambda(X + U) - \gamma\right) + \lambda_C\beta \\ 1, \ f > 0 \\ 0, \ f \leq 0 \end{cases} \quad (15)$$

$$\varepsilon = \begin{cases} g = \partial H/\partial \varepsilon \\ \quad = \lambda(1 + \lambda_U + \alpha\lambda_C)(X + U) \\ \qquad + \lambda_V\left(-\lambda(X + U) - \gamma\right) + \lambda_C\beta \\ 0, \ g < 0 \\ 1, \ g \geq 0. \end{cases} \quad (16)$$

The equations in (15) and (16) denote the optimal beaconing policy of the relay nodes and destinations, respectively. For example, at time t, if $f(t) > 0$, the *beaconing rate* of the relay nodes in the optimal policy is 1, but if $f(t) < 0$, the optimal *beaconing rate* is 0. When $f(t) = 0$, the *beaconing rate* may be any value; hence, there may be many optimal policies, and the policy denoted by (15) is just one of them. Below, we will prove that both the optimal policies for the relay nodes and the destinations denoted by (15) and (16) conform to the *threshold* form.

Before proving the structure of the optimal policies, we first give Lemmas 1 and 2. These lemmas denote some relations of the *costates* and are useful in the proving process of optimal policies (see Lemmas 3 and 4). In the rest of this paper, for any symbol (e.g., X), $X(t)$ also denotes the corresponding expectation $E(X(t))$.

Lemma 1: We have $\lambda_X = \lambda_U$ all the time [the symbols are shown in (12)].

Proof: We define function $l = \lambda_X - \lambda_U$. Then, we have

$$\dot{l} = \dot{\lambda}_X - \dot{\lambda}_U. \quad (17)$$

According to (12), we have

$$\begin{aligned} \dot{l} &= \dot{\lambda}_X - \dot{\lambda}_U \\ &= -\lambda(1 + \lambda_U + \alpha\lambda_C)V\varepsilon - \lambda(\lambda_X + \alpha\lambda_C)Y\mu + \lambda\lambda_Y Y\mu \\ &\quad + \lambda\lambda_V V\varepsilon - (-\lambda(1+\lambda_U+\alpha\lambda_C)V\varepsilon \\ &\qquad - \lambda(\lambda_X + \alpha\lambda_C)Y\mu + \lambda\lambda_Y Y\mu + \lambda\lambda_V V\varepsilon) \\ &= 0. \end{aligned} \quad (18)$$

Therefore, l has the same value all the time. From the *transversality* conditions in (13), we have $l = \lambda_X - \lambda_U = 0 - 0 = 0$. Therefore, l is equal to 0 all the time, and then we have $l = \lambda_X - \lambda_U = 0$. Furthermore, we have $\lambda_X = \lambda_U$ all the time. ■

Lemma 2: We have $z = 1 + \lambda_Y - \lambda_V > 0$ all the time [the symbols are shown in (12)].

Proof: For function z, we have

$$\begin{aligned} \dot{z} &= \dot{\lambda}_Y - \dot{\lambda}_V \\ &= -\lambda(\lambda_X+\alpha\lambda_C)(X+U)\mu + \lambda_Y\left(\lambda(X+U)+\gamma\right)\mu - \lambda_C\beta\mu \\ &\quad - (-\lambda(1 + \lambda_U + \alpha\lambda_C)(X + U)\varepsilon \\ &\qquad + \lambda_V\left(\lambda(X + U) + \gamma\right)\varepsilon - \lambda_C\beta\varepsilon) \\ &= g\varepsilon - f\mu. \end{aligned} \quad (19)$$

Functions f and g are shown in (15) and (16), respectively. Furthermore, we have

$$\begin{aligned} f - g &= \lambda(\lambda_X+\alpha\lambda_C)(X+U) + \lambda_Y\left(-\lambda(X+U) - \gamma\right) + \lambda_C\beta \\ &\quad - (\lambda(1 + \lambda_U + \alpha\lambda_C)(X + U) \\ &\qquad + \lambda_V\left(-\lambda(X + U) - \gamma\right) + \lambda_C\beta) \\ &= \lambda(\lambda_X - 1 - \lambda_U)(X+U) + (\lambda_V - \lambda_Y)\left(\lambda(X+U)+\gamma\right). \end{aligned} \quad (20)$$

From Lemma 1, we have $\lambda_X - \lambda_U$; thus, we can get μ and ε

$$f - g = -\lambda(1 - \lambda_V + \lambda_Y)(X + U) - (\lambda_Y - \lambda_V)\gamma. \quad (21)$$

If $z = 1 + \lambda_Y - \lambda_V \leq 0$, then we have $\lambda_Y - \lambda_V \leq -1 < 0$. Both $X + U$ and γ are nonnegative; therefore, by combining with (21), we can get $f - g \geq 0$. In this case, if $g > 0$, we have $\varepsilon = 1$. Then we have $f > 0$ and $\mu = 1$. Therefore, $g\varepsilon - f\mu = g - f \leq 0$. If $g \leq 0$, from (16), we have $g\varepsilon = 0$. In addition, from (15), we have $f\mu \geq 0$; hence, $g\varepsilon - f\mu \leq 0$. In summary, if $z = 1 + \lambda_Y - \lambda_V \leq 0$, we have $f - g \geq 0$, and then we have $g\varepsilon - f\mu \leq 0$. Based on (19), we have

$$\dot{z} = \dot{\lambda}_Y - \dot{\lambda}_V = g\varepsilon - f\mu \leq 0. \quad (22)$$

Therefore, if $z = 1 + \lambda_Y - \lambda_V \leq 0$, z cannot increase and remain nonpositive all the time. Furthermore, we have $z(T) = 1 + \lambda_Y(T) - \lambda_V(T) \leq 0$. From the *transversality* conditions in (13), we have $z(T) = 1 + \lambda_Y(T) - \lambda_V(T) = 1 + 0 - 0 = 1 > 0$. Therefore, this is a contradiction, and $z = 1 + \lambda_Y - \lambda_V \leq 0$ cannot be correct. In other words, we have $z = 1 + \lambda_Y - \lambda_V > 0$ all the time. ■

Then, we will prove that the optimal policy of the relay nodes denoted by (15) conforms to the *threshold* form. This means that the optimal policy has a *bang-bang* structure. The *bang-bang* structure means that the controlling parameters (*beaconing rates*) just adopt the boundary values (i.e., the maximal value 1 and the minimal value 0), and they can be any value only when they change from one boundary to another [19]. From Lemma 3, we can see that the optimal policy of the relay nodes first adopts the maximal value 1 and then changes to the minimal value 0.

Lemma 3: The optimal policy μ denoted by (15) has at most one jump and it satisfies: $\mu(t) = 1$, $t < h$, and $\mu(t) = 0$, $h \le s \le T$, $0 \le h \le T$. Time h can be seen as the *stopping time*. The *jump* denotes the point where the value of the *beaconing rate* changes.

Proof: For function f denoted in (15), we have

$$\begin{aligned}\dot{f} =& \lambda(\lambda_X + \alpha\lambda_C)(\dot{X} + \dot{U}) + \lambda\dot{\lambda}_X(X + U)\\ &- \lambda\lambda_Y(\dot{X} + \dot{U}) - \dot{\lambda}_Y\left(\lambda(X + U) + \gamma\right)\\ =& \lambda(\lambda_X + \alpha\lambda_C - \lambda_Y)(\dot{X} + \dot{U})\\ &+ \lambda\dot{\lambda}_X(X + U) + f\mu\left(\lambda(X + U) + \gamma\right)\\ =& \lambda(\lambda_X + \alpha\lambda_C - \lambda_Y)(\dot{X} + \dot{U}) + f\mu\left(\lambda(X + U) + \gamma\right)\\ &+ \lambda\left(-\lambda(1 + \lambda_U + \alpha\lambda_C)V\varepsilon\right.\\ &\left.-\lambda(\lambda_X + \alpha\lambda_C)Y\mu + \lambda\lambda_Y Y\mu + \lambda\lambda_V V\varepsilon\right)(X + U)\\ =& \lambda(\lambda_X + \alpha\lambda_C - \lambda_Y)(\dot{X} + \dot{U}) + f\mu\left(\lambda(X + U) + \gamma\right)\\ &+ \lambda\left(-(1 + \lambda_U + \alpha\lambda_C)\dot{U}\right) + \lambda\left(-(\lambda_X + \alpha\lambda_C)\dot{X}\right)\\ &+ \lambda(\lambda_Y\dot{X} + \lambda_V\dot{U})\\ =& \lambda(\lambda_X - \lambda_Y - 1 + \lambda_V - \lambda_U)\dot{U} + f\mu\left(\lambda(X + U) + \gamma\right).\end{aligned} \tag{23}$$

From Lemma 1, (24) is expressed as follows:

$$\dot{f} = -\lambda(1 + \lambda_Y - \lambda_V)\dot{U} + f\mu\left(\lambda(X + U) + \gamma\right). \tag{24}$$

At time s, if $f(s) \le 0$, according to (15), we have $f(s)\mu(s) \le 0$. From Lemma 2, we have $z(s) = 1 + \lambda_Y(s) - \lambda_V(s) > 0$. Therefore, we can get the following equation based on (24):

$$\begin{aligned}\dot{f}(s) =& -\lambda\left(1 + \lambda_Y(s) - \lambda_V(s)\right)\dot{U}(s)\\ &+ f(s)\mu(s)\left(\lambda\left(X(s) + U(s)\right) + \gamma\right) \le 0.\end{aligned} \tag{25}$$

Therefore, function f cannot increase at time s; hence, for time $s+$, which is just bigger than s (meaning that there is no other time between s and $s+$), we have $f(s+) \le f(s) \le 0$. Therefore, the expression in (25) is still correct at time $s+$. In other words, once f is nonpositive at a certain time, it will remain nonpositive all the time. Therefore, if s is the first time that satisfies $f(s) \le 0$, we have $f(t) > 0$, $t < s$ and $f(t) \le 0$, $s \le t \le T$. Furthermore, according to (15), we have $\mu(t) = 1$, $t < s$, and $\mu(t) = 0$, $s \le t \le T$. In this case, the *stopping time* h is equal to s. It is easy to see that the *beaconing rate* of this policy can change its value just at time h; therefore, the optimal policy has at most one point, where it changes its value. This means that there is at most one jump. ■

For the optimal *beaconing rate* ε denoted by (16), we have Lemma 4. From this lemma, we can see that the optimal policy of the destinations also has a *bang-bang* structure, but the changing process is opposite. In particular, it first adopts the minimal value and then changes to the maximal value.

Lemma 4: The optimal policy ε denoted by (16) has at most one jump and it satisfies: $\varepsilon(t) = 0$, $t < h$, and $\varepsilon(t) = 1$, $h \le s \le T$, $0 \le h \le T$. Time h can be seen as the *stopping time*.

Proof: For function g denoted in (16), we have

$$\begin{aligned}\dot{g} =& \lambda(1 + \lambda_U + \alpha\lambda_C)(\dot{X} + \dot{U}) + \lambda\dot{\lambda}_U(X + U)\\ &- \dot{\lambda}_V\left(\lambda(X + U) + \gamma\right) - \lambda\lambda_V(\dot{X} + \dot{U})\\ =& \lambda(1 + \lambda_U + \alpha\lambda_C - \lambda_V)(\dot{X} + \dot{U})\\ &- \dot{\lambda}_V\left(\lambda(X + U) + \gamma\right) + \lambda\dot{\lambda}_U(X + U)\\ =& \lambda(1 + \lambda_U + \alpha\lambda_C - \lambda_V)(\dot{X} + \dot{U}) - \dot{\lambda}_V\left(\lambda(X + U) + \gamma\right)\\ &+ \lambda\left(-\lambda(1 + \lambda_U + \alpha\lambda_C)V\varepsilon - \lambda(\lambda_X + \alpha\lambda_C)Y\mu\right.\\ &\left.+\lambda\lambda_Y Y\mu + \lambda\lambda_V V\varepsilon\right)(X + U)\\ =& \lambda(1 + \lambda_U - \lambda_V - \lambda_X)\dot{X} + \lambda(-\lambda_V)\dot{U}\\ &- \dot{\lambda}_V\left(\lambda(X + U) + \gamma\right) + \lambda(\lambda_Y\dot{X} + \lambda_V\dot{U})\\ =& \lambda(1 - \lambda_V + \lambda_Y)\dot{X} - \dot{\lambda}_V\left(\lambda(X + U) + \gamma\right).\end{aligned} \tag{26}$$

In (12), we can see that

$$\begin{aligned}g\varepsilon =& \lambda(1 + \lambda_U + \alpha\lambda_C)(X + U)\varepsilon + \lambda_V\left(-\lambda(X + U) - \gamma\right)\varepsilon + \lambda_C\beta\varepsilon\\ =& -\dot{\lambda}_V.\end{aligned} \tag{27}$$

Combining with (26), we have

$$\begin{aligned}\dot{g} =& \lambda(1 + \lambda_U - \lambda_V + \lambda_Y - \lambda_X)\dot{X} - \dot{\lambda}_V\left(\lambda(X + U) + \gamma\right)\\ =& \lambda(1 + \lambda_U - \lambda_V + \lambda_Y - \lambda_X)\dot{X} + g\varepsilon\left(\lambda(X + U) + \gamma\right)\\ =& \lambda(1 - \lambda_V + \lambda_Y)\dot{X} + g\varepsilon\left(\lambda(X + U) + \gamma\right).\end{aligned} \tag{28}$$

At time s, if $g(s) \ge 0$, according to (16), we have $g(s)\mu(s) \ge 0$. From Lemma 2, we have $z(s) = 1 + \lambda_Y(s) - \lambda_V(s) > 0$. Therefore, we can get the following equation based on (24):

$$\begin{aligned}\dot{g}(s) =& \lambda\left(1 - \lambda_V(s) + \lambda_Y(s)\right)\dot{X}(s)\\ &+ g(s)\varepsilon(s)\left(\lambda\left(X(s) + U(s)\right) + \gamma\right) \ge 0.\end{aligned} \tag{29}$$

Therefore, function g cannot decrease at time s; hence, for time $s+$, which is just bigger than s (meaning that there is no other time between s and $s+$), we have $g(s+) \ge g(s) \ge 0$. Therefore, the expression in (29) is still correct at time $s+$. In other words, once g is nonnegative at a certain time, it will remain nonnegative all the time. Therefore, if s is the first time that satisfies $g(s) \ge 0$, we have $g(t) < 0$, $t < s$ and $g(t) \ge 0$, $s \le t \le T$. Furthermore, according to (16), we have $\varepsilon(t) = 0$, $t < s$, and $\varepsilon(t) = 1$, $s \le t \le T$. In this case, the *stopping time* h is equal to s, and the optimal policy has at most one jump ■

IV. Simulation and Numerical Results

A. Simulation Results

In this section, we will check the accuracy of the theoretical model, and we run several simulations using the opportunistic network environment (ONE) simulator [28]. Because the goal is to check the accuracy of our theoretical model, we assume that the total energy budget is not limited, and we compare the value of $E(C(T))$ (the total energy consumption) predicted by our theoretical model and that obtained through simulations in three different scenarios. Simulation in the first scenario is based on the random waypoint (RWP) mobility model, which is commonly used in many mobile wireless networks [29]. Here, we select 500 relay nodes and 50 destinations. These nodes move according to the RWP mobility model within a 10 000 m $\times$ 10 000 m terrain according to a scale speed chosen from a uniform distribution from 4 to 10 m/s. The transmission range of these nodes is 50 m. In the second scenario, we use a Poisson contact process with $\lambda = 3.71 \times 10^{-6}\mathrm{s}^{-1}$ to generate node contact events. In particular, the value of λ is obtained from the vehicle model, which is based on the real motion trace from about 2100 operational taxis for about one month in Shanghai city collected by GPS [30]. The location information was recorded at every 40 s within an area of 102 km^2. By analyzing a large amount of the trace data, Zhu *et al.* [24] find that the exponential distribution with $\lambda = 3.71 \times 10^{-6}\mathrm{s}^{-1}$ can fit the Shanghai city motion trace very well. For the Poisson contact scenario, we also generate 550 nodes. Among these nodes, we randomly select 50 nodes as the destinations and other nodes are the relay nodes. The Poisson contact model is a synthetic model, in which the number of contacts conforms to the Poisson distribution and the parameter is λ here. Therefore, we use the value $3.71 \times 10^{-6}\mathrm{s}^{-1}$ to generate the contact events according to the Poisson distribution, and the contact events are the inputs of the ONE simulator. Then, the simulator makes a beaconing decision in every contact event according to the beaconing policy. For example, for a contact event at time t, the relay nodes beacon with probability $\mu(t)$. In the third scenario, we use the famous Infocom'05 motion trace, which includes 41 nodes [31]. We randomly select ten nodes as the destinations, and others are the relay nodes. Different from the Poisson contact model, in this scenario, the original trace is divided into discrete sequential contact events. After getting the contact events, other things are the same as that in the second scenario.

For the theoretical related parameters, there are many settings and we cannot carry out the simulation in every setting. Here, we just consider certain specific cases as the examples. In particular, we consider two cases. In Case 1, we have $(\mu(t), \varepsilon(t)) = (1, 1)$, $0 \le t \le T$, but in Case 2, we have $(\mu(t), \varepsilon(t)) = (0.5, 0.5)$, $0 \le t \le T$. In Case 1, nodes meet each other according to the exponential distribution with parameter λ. However, in Case 2, the parameter is 0.5λ. On the other hand, both α and β are the system-specified positive constants that weight the energy consumption of each transmission and each beaconing process, respectively. Their values are related to the system; hence, they can have different values in different applications. For simplicity, many works just assign a value to them. For example, the works in [14] and [15] let $\alpha = 1$. In this section, we just check the accuracy of our model so that we can assign them a certain value directly, too. In particular, we let $\alpha = 1$ and $\beta = 10^{-5}$. In addition, the maximal death rate $\gamma = 10^{-5}$. The maximal lifetime of the message T increases from 0 to 5000 s, and the interval is 200 s. In other words, we carry out the simulation each 200 s. Therefore, we carry out $5000/200 = 25$ simulations in each scenario. In the nth simulation of any scenario, the maximal lifetime T is equal to $200n$ s, and the length of the simulation is T. In each simulation, just one message is generated, but each simulation repeats 30 times. Therefore, we can get 30 samples for each simulation, and each sample denotes the energy consumption in the simulation. Based on these samples, we can get the average energy consumption and the confidence interval with confidence level 0.95. The whole results based on above three scenarios are shown in Figs. 1–3, respectively.

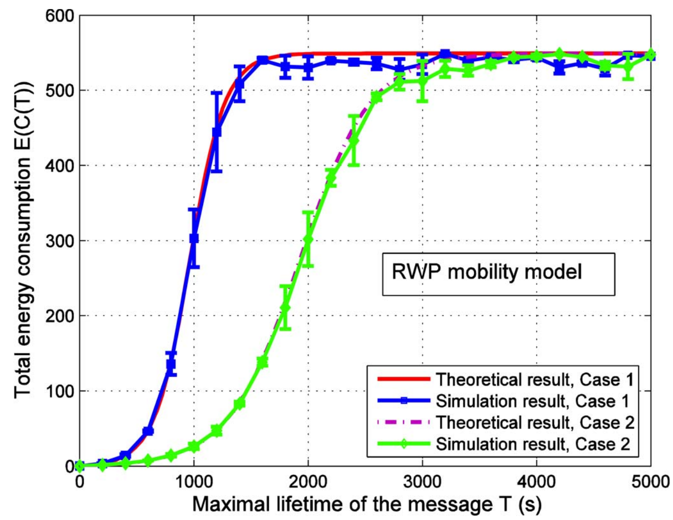

Fig. 1. Simulation and theoretical results comparison with RWP model. The vertical bars denote the confidence interval with confidence level 0.95.

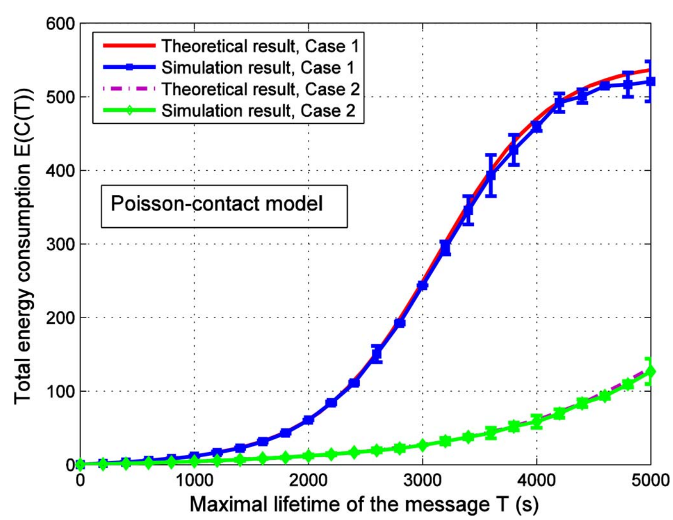

Fig. 2. Simulation and theoretical results comparison with Poisson contact model. The vertical bars denote the confidence interval with confidence level 0.95.

The results in Figs. 1 and 2 show that the deviation between the theoretical results and simulation results is very small. For example, the average deviation in the RWP model is about 4.35% and only 3.01% in the Poisson contact mobility model. This demonstrates the accuracy of our theoretical models.

The average deviation in Fig. 3 is bigger than that in Figs. 1 and 2, and it is about 6.85%. In fact, some works have shown that the intermeeting time in INFOCOM'05 motion trace does not conform to the exponential distribution accurately and may have a power law and exponential decay distribution [22]. However, our theoretical framework is based on the exponential

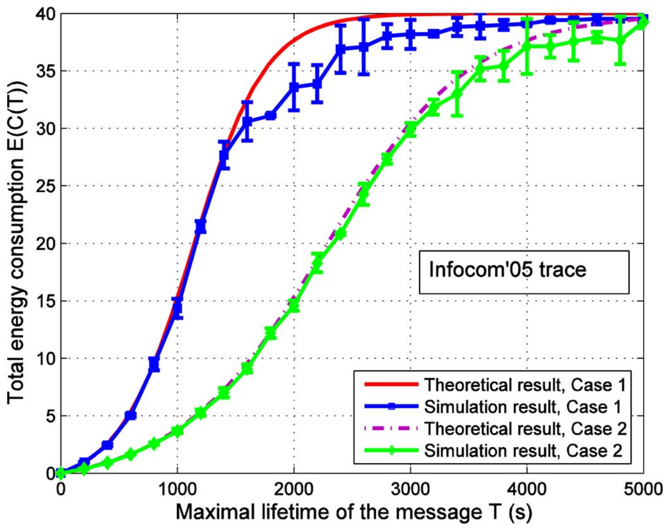

Fig. 3. Simulation and theoretical results comparison with Infocom'05 trace. The vertical bars denote the confidence interval with confidence level 0.95.

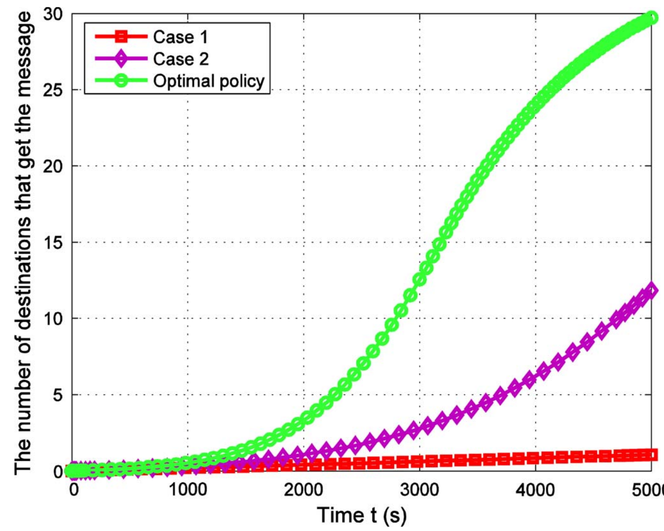

Fig. 4. Performance comparison with different policies.

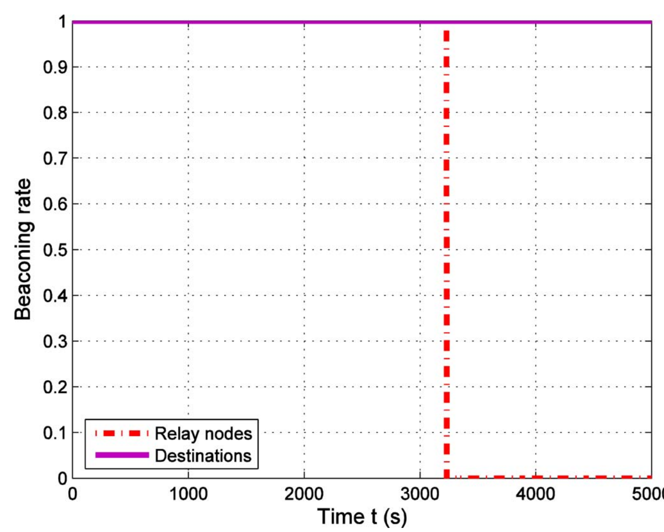

Fig. 5. Optimal policy for both the relay nodes and destinations.

model; hence, we have to use the exponential model to fit the motion trace, and this will bring bigger deviation. On the other hand, the deviation is not too bigger; thus, the result also shows that our theoretical framework may be feasible in some cases where nodes do not move according to the exponential model.

B. Performance Analysis With Numerical Results

We use $\lambda = 3.71 \times 10^{-6}\text{s}^{-1}$ to get all of the numerical results and compare the performance of the optimal policy obtained by our model with the performance of other policies. Note that at any time t, $\mu(t)$ is a stochastic variable whose value belongs to [0, 1]. Therefore, there are infinite beaconing policies for the relay nodes. Similarly, there are also infinite beaconing policies for the destinations; hence, we cannot give the numerical result of every policy. In this paper, we mainly consider another special policy, in which the destinations beacon with the maximal rate all the time, but the relay nodes' *beaconing rate* is p. In particular, we have $(\mu(t), \varepsilon(t)) = (p, 1)$ all the time, and p is a constant, which belongs to [0,1]. In particular, each value of (p, 1) corresponds to one specific policy. Here, we just use two of them. In the first case, we have $p = 0$ all the time. However, under the second policy, we have $E(C(T)) = B$. In this case, the value of p can be easily obtained based on our theoretical model by the MATLAB ODE suite. In summary, in Case 1, we have $(\mu(t), \varepsilon(t)) = (0, 1)$ all the time. In Case 2, we have $(\mu(t), \varepsilon(t)) = (p, 1)$ all the time, and under this policy, we have $E(C(T)) = B$. However, for the policy in Case 2, if we still have $E(C(T)) < B$ when $p = 1$, the policy of Case 2 is (1, 1). Let the maximal energy budget B be 100, and other settings are the same as those in the simulation. Based on these settings, we can get Fig. 4.

The result in Fig. 4 shows that the performance of our optimal policy is much better than that of other policies. Lemmas 3 and 4 show that the optimal policy for both the relay nodes and destinations conforms to the *threshold* form. We can see the phenomenon in Fig. 5 more clearly. The result shows that the optimal policy of the relay nodes conforms to the *threshold* form. However, for the destinations, they will beacon with the maximal rate all the time, and the optimal policy does not have any jump. In fact, this result also conforms to Lemma 4, and the stopping time $h = 0$. Therefore, the result in Fig. 5 shows that both Lemmas 3 and 4 are correct.

Then, we will explore the performance when the total energy B is different. In particular, we let B increase from 30 to 300. Other settings are the same as those in Fig. 4. Note that, in Case 1, we have $(\mu(t), \varepsilon(t)) = (0, 1)$ all the time; hence, the performance does not vary with B. For this reason, we just compare the performance of our optimal policy with that of Case 2. Then we can obtain Fig. 6. From the result, we can see that our optimal policy is still better.

Now, we want to study the impact of the maximal death rate. In particular, we let increase from $\gamma = 10^{-5}$ to $\gamma = 10^{-4}$. The value of B is 100, and other settings are the same as that for Fig. 6. Then, we can obtain Fig. 7. This result shows that our optimal policy is better too. In addition, the result shows that the performance is decreasing with the maximal death rate of nodes.

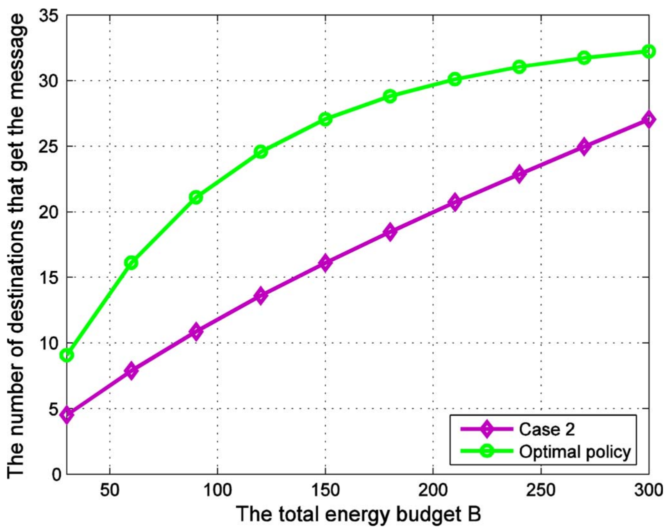

Fig. 6. Performance comparison with different policies when the total energy B is different.

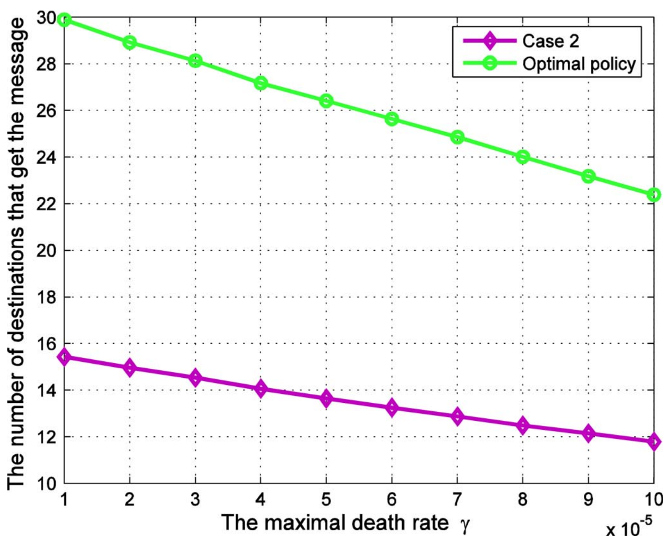

Fig. 7. Performance comparison with different policies when the maximal death rate γ is different.

V. Conclusion

Energy constraint beaconing control of ER algorithm has been popular recently. However, state-of-the-art works often assume that there is only one destination. In this paper, we have studied the optimal beaconing control in DTNs with multiple destinations. In particular, we classify the *beaconing rates* according to the roles of nodes (relay nodes or destinations) and explore the optimal beaconing policies for the relay nodes and destinations, respectively. First, we present a theoretical model to evaluate the performance under different *beaconing rates*. Based on the model, we formulate the corresponding optimization problem. Through Pontryagin's maximum principle, we obtain the optimal beaconing policies and prove that both the optimal policies conform to the *threshold* form. In other words, the optimal policies have a *bang-bang* structure and they are easy to use. However, the jumping process for the relay nodes is opposite for the destinations. For example, the relay nodes first have the maximal *beaconing rate* and then change to the minimal *beaconing rate*, but the optimal policy for the destinations jumps from the minimal value to the maximal value. We check the accuracy of our theoretical model through simulations. In addition, we compare the performance of the optimal policies with certain other policies through extensive numerical results and find that the optimal policies obtained by our model are better.

The duty cycle operation regarding the variation of "on–off" status for nodal radio interface is very important [32]. In addition, the contacts between nodes may be predicted, and then one can design the efficient beaconing policy based on the prediction. For example, the work in [33] proposes a wakeup scheduling policy, in which a node stays asleep during intercontact times when contact probing is unnecessary and only wakes up when a contact with another node is likely to happen. In the future, we want to combine above problems with our work and design more efficient beaconing algorithms. In addition to the optimal beaconing problem, there is also the optimal forwarding problem. Therefore, the routing policy can have important impact. At present, there are many routing policies [34]; therefore, we want to combine the corresponding routing algorithms when considering the optimal beaconing or the joint beaconing and forwarding policies.

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